The Role of Emotion in Problem Solving: First Results from Observing Chess

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Author version

Abstract

In this paper we present results from recent experiments that suggest that chess players associate emotions to game situations and reactively use these associations to guide search for planning and problem solving. We describe the design of an instrument for capturing and interpreting multimodal signals of humans engaged in solving challenging problems. We review results from a pilot experiment with human experts engaged in solving challenging problems in Chess that revealed an unexpected observation of rapid changes in emotion as players attempt to solve challenging problems. We propose a cognitive model that describes the process by which subjects select chess chunks for use in interpretation of the game situation and describe initial results from a second experiment designed to test this model.

Keywords: Working memory, Concept Formation, Chunking, Situation Modeling, Emotions, Problem Solving

1 Introduction

Humans display awareness and emotions through a variety of non-verbal channels. It is increasingly possible to record and interpret such information with available technology. Publicly available software can be used to efficiently detect and track face orientation using web cameras. Concentration can be inferred from changes in pupil size [19]. Observation of Facial Action Units [11] can be used to detect both sustained and instantaneous (micro-expressions) displays of valence and excitation. Heart rate can be measured from the Blood Volume Pulse as observed from facial skin color [25]. Body posture and gesture can be obtained from low-cost RGB sensors with depth information (RGB+D) [29] or directly from images using detectors learned using deep learning [26]. Awareness and attention can be inferred from eye-gaze (scan path) and fixation using eye-tracking glasses as well as remote eye tracking devices [16]. Such recordings can be used to reveal awareness of the current situation and to predict ability to respond effectively to opportunities and threats.

We have constructed an instrument for capturing and interpreting multimodal signals of humans engaged in solving challenging problems. Our instrument, shown in Figure 1, captures eye gaze, fixations, body postures, and facial expressions signals from humans engaged in interactive tasks on a touch screen. We use a 23 inch Touch-Screen computer, a Kinect 2.0 mounted 35 cm above the screen to observe the subject, a 1080p Webcam for a frontal view, a Tobii Eye-Tracking bar (Pro X2-60 screen-based) and two adjustable USB-LED for lighting condition control. A wooden structure is used to rigidly mount the measuring equipment in order to assure identical sensor placement and orientation for all recordings.

Several software systems have been used for recording and analyzing data in our pilot experiment. Tobii Studio 3.4.7 was used for recording and analysis of eye-gaze. Noldus FaceReader 7.0 was used for emotion detection. Body posture was provided by both the Kinect 2.0 SDK and by an enhanced version of a real-time multi-person pose estimation software [6]. This can be used to observe number of indicators for stress from

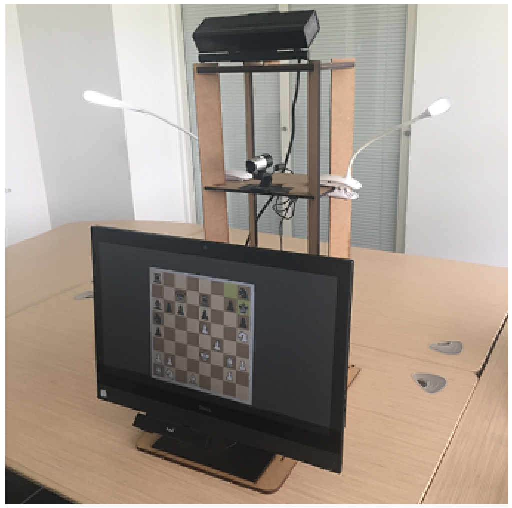


Figure 1: Instrument for recording gaze and emotions of experts engaged in solving problems. On top, a Kinect2 oriented at the player. In the middle, a USB camera to capture the face. Illumination is provided by two LED lamps on the sides. A wooden structure is used to provide a fixed position and orientation for all sensors.

body posture including agitation, body volume and self-touching. Body Agitation was computed from the intensity of joint rotations. Body volume is the space occupied by the 3D bounding box built around joints [17]. Self-Touching was determined from collisions between wrist-elbow segments and the head, and is known to be correlated with negative affect as well as frustration in problem solving [14].

As a pilot study, we observed expert chess players engaged in solving problems of increasing difficulty [13]. During the study, data were recorded from all sensors (Kinect 2, Webcam, Screen capture, user clicks, Tobii-Bar) using the RGBD Sync SDK from the Mobile RGBD project. This framework provides synchronization of all data by associating a timestamp with a millisecond precision to each recorded frame and can be used to read, analyze and display recorded data. Our initial hypothesis was that we could directly detect awareness of significant configurations of chess pieces (chunks) from eye-scan and physiological measurements of emotion in reaction to game situation. The pilot experiment demonstrated that this initial hypothesis was naive. This paper reports on our attempts to provide interpretations of those results, as well as a more recent set of experiments aimed at confirming our interpretation.

2 Results from the First Pilot Experiment

A first pilot experiment was designed to validate our instrument and to evaluate the effectiveness of different systems and sensors for observing eye-gaze, facial expressions, body posture, pupil dilation, and cardiac rhythm. With the aid of the president of a local chess club, we defined 11 end-game chess problems, similar to the daily chess puzzles that can be found in magazines or on chess websites. Each of these tasks challenges the subject to check-mate the opponent in a number of predefined moves ranging from 1 to 6. Tasks requesting 1 to 3 moves are viewed as easy whereas tasks requiring 4 to 6 moves are considered to be challenging. We ordered the problems in increasing difficulty with 4 tasks with one move, 4 tasks with two and three moves (2 of each) and 3 tasks with four, five and six moves to mate. The tasks were presented with the subject alternately playing black or white. Full results with eye-gaze and fixation are discussed in [13]. Here we concentrate on observations of emotion.

2.1 Data Collection

Subjects were asked to solve chess tasks within a fixed, but unspecified, time period. We recorded eye gaze, facial expressions, body postures and physiological reactions of the players as they solved problems of increasing difficulty. In a recording session with the local chess club, we recorded 21 subjects solving the problems. Unfortunately 7 of the recordings were unusable because of problems with eye-tracking. A few weeks later we had the opportunity to test 9 additional subjects during a local tournament, including six casual players who were not currently playing in club. These two sessions yielded a total of 22 useful recordings. All of our subjects have Elo ratings[1], with 9 experts (Elo ratings from 1759 to 2150) and 14 intermediates level players (Elo 1100 to 1513).

Participants were tested individually in sessions lasting approximately 45 min. Subjects were made aware of the eye-tracking bar in order to perform a calibration step. No other information was given about the recording equipment. After providing informed consent from each subject, the Lichess web platform was presented and participants were asked to play a practice game against a weak opponent provided by the Stockfish[2] game engine playing at level 1. No recording was made during this first game.

Each subject was individually presented with the N-Check-Mate tasks. The number of moves needed for the N-Check-Mate tasks was communicated to the subject and subjects were informed of an unspecified time limit. The time constraints range from 2 min for the easiest tasks (1–2 moves) to 5 min for the most challenging tasks (4–5–6 moves). Subjects knew only that they were limited to a few minutes to solve the task, although an announcement was made when only one minute was remaining. If the subject was unable solve the task within the time limit, the task was considered as failed and the experiment proceeded to the next task. The experiment is considered complete once all tasks had been completed.

2.2 Data Analysis

The Noldus FaceReader software [21] was used to obtain both sustained and instantaneous (micro-expression) displays of emotion, as well as cardiac rate using Blood Volume Pulse. FaceReader uses the Viola Jones face detector [32] to locate the largest face in the field of view in order to detect motion of 20 Facial Action Units. Each action unit is assigned a score between 0 and 1 and these are used to classify the subject's emotions into one of Ekman's six basic emotion states[3]. We were able to use the basic emotions provided by Noldus to estimate values for Valence and Arousal. Self-Touching is determined from collisions between wrist-elbow segments and the head.

During the pilot experiment, we encountered many cases where the face detector used by FaceReader failed, primarily due to head movements or occlusions. Comparative experiments with OpenFace 2.0 [4] using data recorded in the pilot demonstrated that OpenFace provided more reliable detection and tracking of faces as well as reliable tracking of facial action units [3]. For subsequent experiments we have moved to using Open Face 2.0.

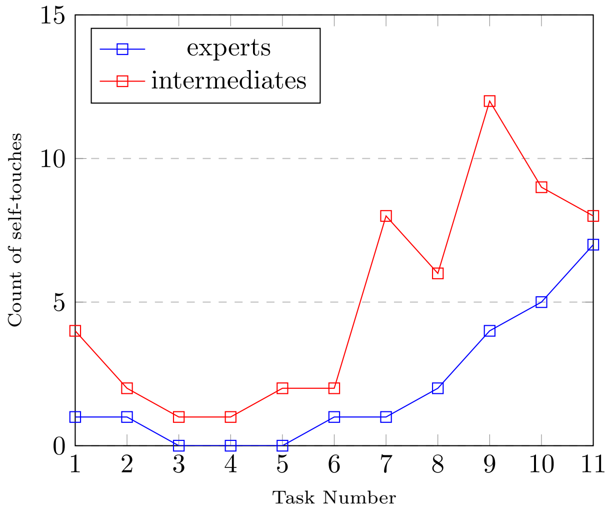
2.3 Results from the pilot experiment

Figure 2 shows the number of self-touches and changes of emotion for intermediate and expert players over our increasingly challenging problem set. Our initial hypothesis was that subjects would exhibit sustained displays of emotions ranging from pleasure to frustration as the difficulty of the problems increased. We were surprised to observe that this was not the case. Rather, both self-touching and rate of change in emotion state evolved from a neutral emotion during reactive play to a period of frequent touching and rapid changes in emotion as the problems became more challenging.

[1] Elo ratings are an open ended scale used to rate chess players based on tournament performance. The system is named after its creator, Arpad Elo, a Hungarian-American physics professor.

[2] Stockfish is an open-source game engine used in many chess software systems, including Lichess. Stockfish levels range from level 1 (easiest) to level 8 (most challenging).

[3] Happiness, sadness, anger, fear, disgust, surprise and neutral.



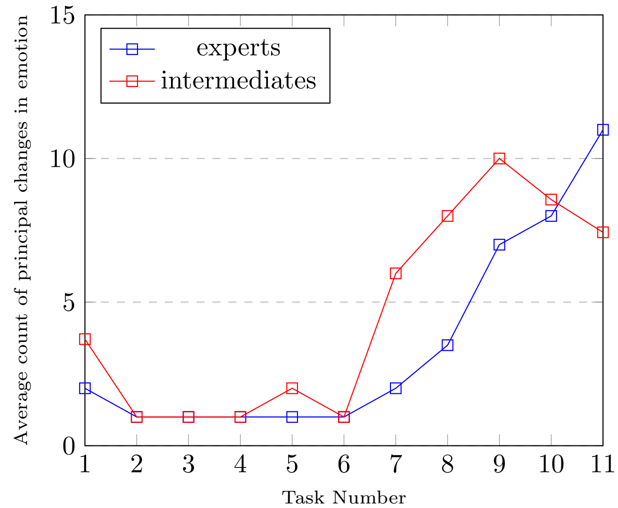


Figure 2: Self-touches (left) and average count of number of changes in emotion state (right) for intermediate and experts over the 11 tasks.

Figure 2 illustrates that the rate of changes of emotional state increases with the difficulty for both intermediates and experts, with significantly higher numbers for intermediate players. The correlation with the rise in self-touching, confirms that subjects were increasingly challenged. We conclude that frustration for intermediate players rose rapidly for tasks 7, 8, 9 and 10, and then dropped, as subjects seemed to abandon efforts to solve task 11. For experts, self-touching and changes in emotion gradually increased for problems 7 through 11, indicating that experts experienced only minor discomfort for these problems.

3 A Cognitive Model for Reasoning about Chess

Our initial hypothesis was that rapid changes of emotion correspond to success or failure of alternative branches during game tree exploration. We now believe that this explanation is overly simplistic. Even expert players are unable to hold the entire game state in working memory [12]. The selection of the partial game description to hold in working memory is critical for reasoning about chess.

In order to better understand the phenomena observed in our pilot experiment, we have constructed a model of the cognitive processes involved, using theories from cognitive science and classic (symbolic) artificial intelligence. This model is a very partial description that allows us to ask questions and make predictions to guide future experiments. Our model posits that experts reason with a situation model that is strongly constrained by limits to the number of entities and relations that may be considered at a time. This limitation forces subjects to construct abstract concepts (chunks) to describe game play, in order to explore alternative moves. Expert players retain associations of situations with emotions in long-term memory. The rapid changes in emotion correspond to recognition of previously encountered situations during exploration of the game tree. Recalled emotions guide selection of situation models for reasoning. This hypothesis is in accordance with Damasio's Somatic Marker hypothesis, which posits that emotions guide behavior, particularly when cognitive processes are overloaded [9].

3.1 Situation Models

Situation models [18] provide a formal framework for describing human comprehension and problem solving. In logic terms, a situation model is a state graph, in which each state (situation) is defined as a logical expression of predicates (relations) defined over entities. Entities can represent observed phenomena as well as instances of concepts, procedures or episodes from long-term memory. A change in the relation between entities results in a change in situation. Procedures and actions may be associated with situations for use in planning and reasoning [5]. Consequences may also be associated with situations, making it possible to anticipate opportunities and threats.

Relations describe associations of entities. Examples include spatial or temporal order relations [1], as well as ownership and family or social associations. The number of arguments of a relation is called its arity. Formally, a relation can be defined with any number of arguments, including zero. In semantic web tools such as RDF and OWL, arity 2 predicates are used to relate a subject to a property (an object), expressed with the following schema: (Subject Relation Object). However, in many domains, including chess, it is necessary to use relations with different arities.

3.2 Concept Schema for Entities and Relations

Formal representations of concepts can be expressed as frames [24]. Frames define abstract concepts that can be instantiated as entities. A frame associates the entity class with a set of properties, and a set of procedures. Formally, the properties and procedures associated with a concept can be seen as a form of relation [31]. However, the association of properties within a concept is internal and immutable. The values may change, but the set of properties and procedures are fixed. Changing the set of properties or procedures generates a new concept.

The basic entities in chess are the individual pieces with properties that can include the type of piece, color (white or black), and board position. This can be defined as a frame using the following schema:

```
(ChessPiece (piece-ID)
    (kind (one-of (king, queen, bishop, knight, rook, pawn)))
    (color (one-of (black white)))
    (position (row (range 1 to 8) (column (range a to h))
    (actions (move-procedure))
)
```

Recognition of a concept creates an instance of the concept as an entity in the situation model. Entities are labeled with a unique identity (piece-ID) that can be used as a reference in instantiating relations. Move-procedure is a procedure for generating the set of legal moves for the piece.

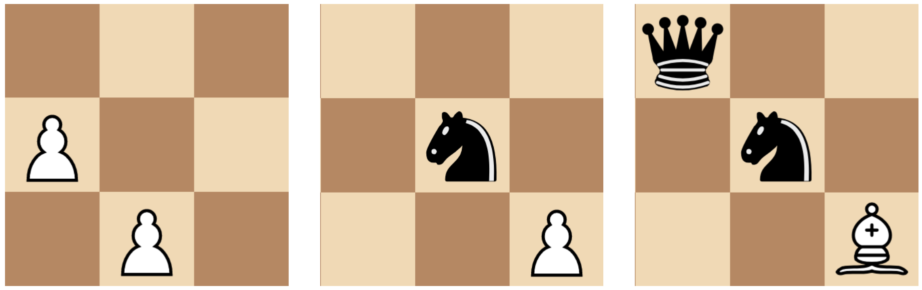
The board configuration can be understood as a collection of relations in which pieces threaten pieces of the opposing color and defend pieces of the same color. As with entities, relations are instances of abstract concepts defined as frames. A concept schema for a binary (arity-2) chess relation would be:

```
(Relation (Relation-ID)
    (Name (relation-name))
    (Kind (one-of (offensive, defensive)))
    (Subject (entity-ID))
    (Object (entity-ID))
)
```

Relations can be defensive, in which a piece protects or defends another piece of the same color, or offensive in which a piece threatens a piece of an opposing color. The subject and object are pointers to instances of pieces or chunks that are held as entities in situation model.

A concept schema for an arity-3 relation would be:

```
(Relation (Relation-ID)
    (Name (relation-name))
    (Kind (one-of (offensive, defensive)))
    (Subject (entity-ID))
    (Object1 (entity-ID))
    (Object2 (entity-ID))
)
```



a) protects	b) threatens	c) pins

Figure 3: Three examples of relations. a) A defensive binary relation: (pawn protects pawn) b) An offensive binary relation: (bishop threatens knight) c) an offensive ternary relation: (bishop pins knight to queen)

Figure 3 shows examples of chess relations. Figure 3a is a binary defensive relation "protects", while 3b is a binary offensive relation "threatens". Both of these can be expressed in terms of the classic binary relation schema (subject relation object). Figure 3c shows a ternary (arity-3) relation: "pins" with a subject and two objects.

Note that for every binary relation there is an inverse relation where the object and subject roles are switched. For example (pawns threatens knight) implies an inverse relation (knight threatened-by pawn). For arity-3 relations, there are 6 inverse relations, one each for each possible permutation of the subject, object1, and object2. Each relation constrains possible moves by the subject piece.

3.3 Working Memory

Limits on the size of working memory are a fundamental property of human cognition. In a seminal paper, G.A. Miller demonstrated that humans could simultaneously retain between 5 and 9 things in short-term working memory [23]. Most authors present working memory (WM) as a collection of buffers that represent propositions representing perceived phenomena or associated concepts from long-term memory (LTM). Cowan [8], reviews the history of research on working memory, discussing the variety of definitions and experimental demonstrations that have been used to describe this phenomena. Many authors report that human adults are limited to 3 or 4 meaningful modal percepts (visual, auditory, tactile, or propositional) and that unrehearsed percepts decay within about 30 seconds.

Working memory is generally modeled as a form of Hebbian active memory [15], [22] with propagation of activation energy providing associations with other working memory elements, perception, actions, and long-term memory. As activation energy spreads from WM into LTM, multiple paths can lead to accumulations within cognitive units in LTM [2]. When activation energy for a cognitive unit in LTM exceeds the activation of an entity in WM, the LTM unit replaces the contents of the WM unit. This can potentially impose a third limit on working memory: a limit on the number of associations for an entity, as excessive associations can dissipate the activation energy of a WM unit.

We note that activation energy may not be the only mechanism involved in determining working memory contents. Cognitive skills such as mental arithmetic or chess may involve automatically scanning through a set of possible situation models in a predefined sequence.

3.4 Representing Chess Concepts with Chunks

The size of working memory limits the complexity of the description of game state that a subject can retain and recall. Beginning players tend to see the game in terms of the situations of individual pieces. Viewed this way, the game state rapidly becomes extremely complex, as a large number of pieces generate an even larger number of defensive and offensive relations. Beginning players are blinded to possible opportunities and threats by an overwhelming flood of information. Learning to play involves learning to see the game in terms of configurations of pieces, referred to as chunks.

Chunks are long-term memory constructs used for perception, recall and reasoning about chess configurations. Figure 4 gives three examples of chess chunks. The term was originally proposed in 1946 by De Groot [10] as a form of cognitive unit used for reasoning by chess masters. Each chunk is a distinct concept that can be directly recognized by a player and represented as a unique entity in working memory. Chunks allow players to accommodate the limits imposed by working memory.

Chase and Simon [7] explored the use of chunks for perception and recall by players of different levels, and demonstrated the existence of chunks with memory experiments in which players with different levels of expertise were required to remember configurations of pieces. Simon and Gilmartin [30] estimate that expertise in chess may require between 10,000 and 100,000 chunks in long-term memory. This rich vocabulary enables players to determine good moves with only moderate search of the game tree.

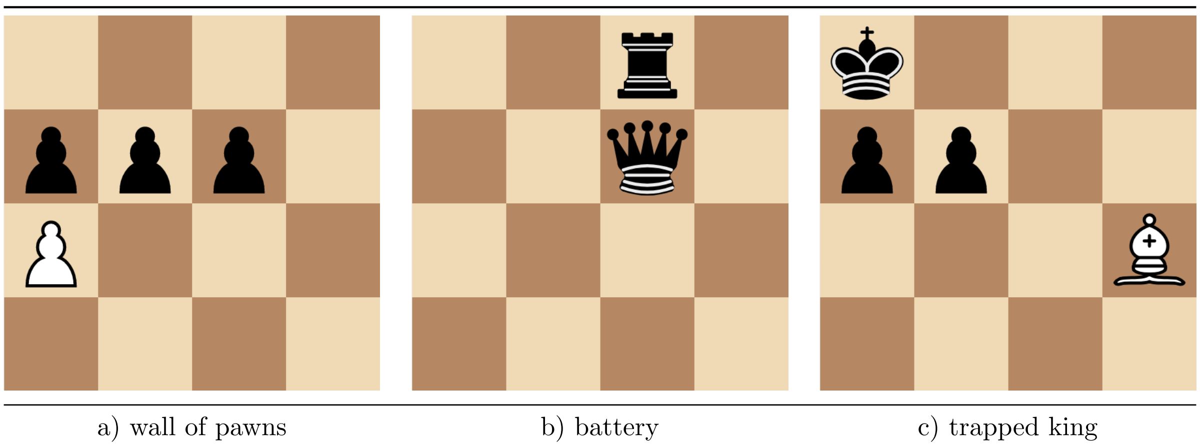


Figure 4: Three examples of chess chunks. a) a wall of black pawns. b) a battery in which a rook defends an attacking queen. c) A trap in which a bishop prevents motion by the opposing king offering a potential checkmate if a second threatening piece and be added to the situation.

3.5 A Situation Model for Chess

The following is a possible schema for chess situations. Entities may be instances of pieces or chunks. The actions slot provides a list of possible moves that are enabled or prevented by the situation. The emotion slot provides values for valence, arousal and dominance acquired from experience and used to guide reasoning.

```
(ChessSituation (Situation-ID)
    (color (one-of (black, white)))
    (relations (Relation-ID*))
    (entities (Any-of (Piece-ID, Chunk-ID)*)
    (moves (moves*))
    (emotion (valence, arousal, dominance))
)
```

The symbol * indicates a list of one of more elements. The number of entities and relations within a situation is limited by the number or elements in working memory. This number should not exceed Miller's limit and is likely to be much smaller as part of working memory will be consumed by other information about the game context such as imminent threats or time constraints. For example, when considering consequences of a move, the player must retain the current situation, the candidate move and the resulting situation in working memory, as well as other information about the game context. This would seem to limit the game situation model to 3 or at most 4 entities. For example, a typical situation model may be composed of one defending chunk, one attacking chunk and a single active piece.

De Groot proposed that chess reasoning consists of 4 stages: Orientation, Exploration, Investigation and Validation. Scan paths observed in our experiments tend to confirm these phases. During the orientation phase, players perceive chunks that can be used to model the situation. Beginners tend to fixate on individual pieces, while expert players can be observed to fixate on the center of chunks, but make only very rapid saccades in the direction of component pieces. Small subsets of chunks are then selected and used to explore possible moves. This raises the question of how the player can select from among the large available set of chunks. We believe that emotion plays a critical role in such selection.

4 The Role of Emotion in Reasoning

Our current hypothesis is that the rapid changes in emotion displayed by subjects in our pilot experiment are an involuntary display in reaction to recognition of previously encountered situations during exploration of the game state. With this interpretation, the player rapidly considers partial descriptions as situations composed of a limited number of perceived chunks. Recognition of situations from experience evokes emotions that are displayed as face expressions and body posture. Our hypothesis is that the subject uses the evoked emotions to select from the many possible situations for reasoning about moves during orientation and exploration.

4.1 Observing and Modeling Human Emotions

Ekman [Ekman 77] observed that emotions are expressed by coordinated temporal activations of 21 different facial muscles assisted by a number of additional muscles. Activations of these muscles are visible through subtle deformations in the surface structure of the face. Ekman proposed a formal coding system (Facial Action Coding or FACS) that can be learned by humans and has been used to produce relatively reliable software to detect facial muscle activations.

Ekman also proposed that six emotion states (joy, sadness, anger, disgust, fear and surprise) are universal across cultures [Ekman 92]. As an alternative to recognizing emotions as states, a number of investigators have proposed that emotions can be observed as physiological parameters [28]. The circumplex model [27] represents emotions as trajectories in a circular space with two dimensions: arousal and valence. The center of the circle represents a neutral valence and a medium level of arousal. A third dimension is required to discriminate between anger and fear. Russel and Mehrabian refer to this as dominance. This is closely related to frustration as measured by self-touching as measured in our experiments.

4.2 Emotions as a Guide for Reasoning in Chess

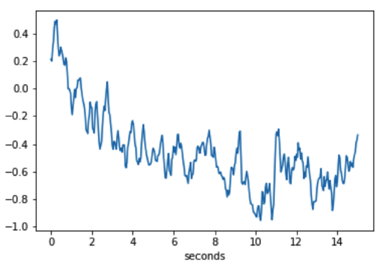
Valence, arousal and dominance can serve to guide reasoning in chess. These three values can be learned from experience and associated with chess situations in long-term memory.

Dominance corresponds to the degree of experience with the recognized situation. As players gain experience with alternate outcomes for a situation, they become more assured in their ability to spot opportunities and avoid dangers. Valence corresponds to whether the situation is recognized as favorable (providing opportunities) or unfavorable (creating threats). Arousal corresponds to the imminence of a threat or opportunity.

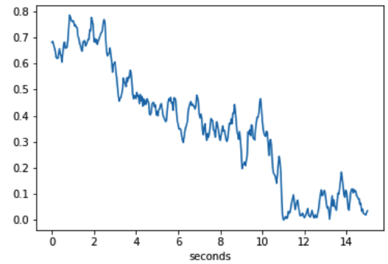
With this model, a defensive player will give priority to reasoning about unfavorable situations and associated dangers. An aggressive player will seek out high valence situations. All players will give priority to situations that evoke strong arousal. The amount of effort that player will expend exploring a situation can determined by dominance.

5 A Second Experiment to Develop our Model

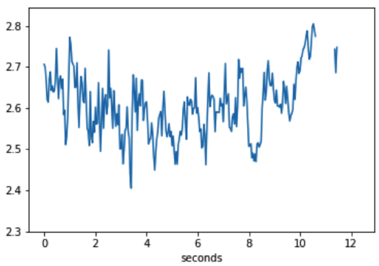
In order to develop our model, we have conducted a second experiment in which we players were asked to explain their reasoning. The objectives were to determine if eye-gaze, valence, arousal and frustration could be correlated with the four phases of reasoning proposed by De Groot, and to construct an ontology for chess concepts (chunks and relations) used by players.



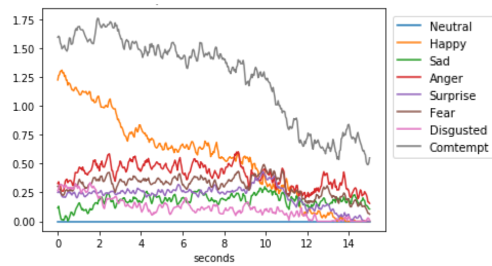
a) Valence



b) Arousal



c) Pupil Diameter



d) Emotion States

Figure 5: Subject Q6 (expert ELO 1950+) solving task 4 (medium difficulty). The subject rapidly recognized and confirmed the solution, a shown by a steady decrease in valence, arousal and contempt. A rise in pupil size is evident during the final, confirmation phase.

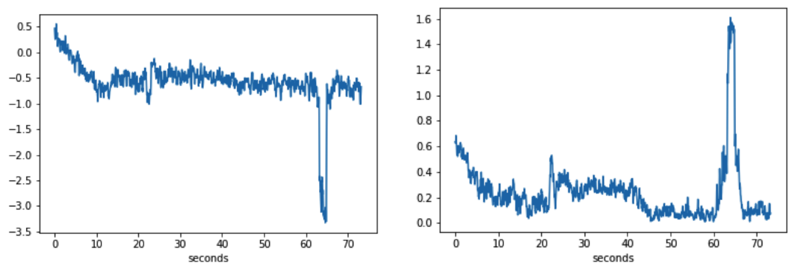
These experiments were performed using OpenFace 2.0 for recording Facial Action Units (AUs) and the EyeWorks software for measuring pupil dilation. Ekman's basics emotions were computed from the AUs following Ekman's formula [11]. Valence was computed as the intensity of AUs involved in positive emotions, minus intensity of AUs involved in negative emotions. Arousal was computed as a combination of AUs averaged over the last 60 seconds.

We considered two techniques for self-reporting: Concurrent Verbal Analysis (CVA) and Retroactive Task Explanation (RTE) [20]. With CVA, subjects are asked to think aloud and to explain their reasoning as they solve the task. With RTE, subjects are asked to explain their reasoning after completing each task. Both techniques have possible problems. With CVA a part of working memory is devoted to constructing the explanation, reducing the cognitive resources available for resolving the task. With RTE, the subject may invent an explanation that does not accurately reveal the cognitive process that was used. After a short pilot experiment with 4 subjects, we elected to use RTE.

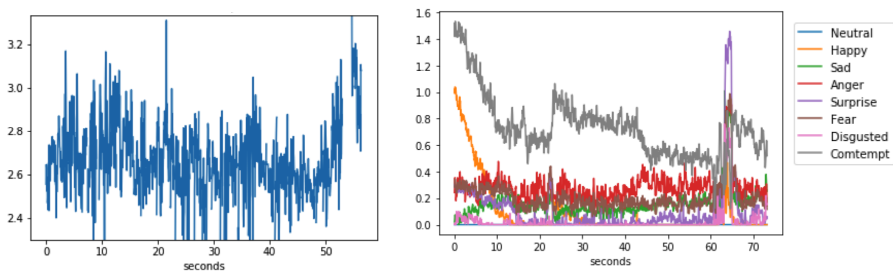
For our second experiment we recruited 23 subjects (2 experts, 19 intermediates and 2 beginners). Expert players were active players with Elo ratings from 1930 to 2000. For the intermediate players, the Elo ratings ranged from 1197 to 1700. Twelve of the intermediates were casual players who were not currently playing in club.

Subjects were initially asked to play two easy practice games to become familiar with the equipment. We then recorded eye-gaze, emotional state, pupil size, valence, arousal, and self-touching as subjects solved a series of 7 tasks composed of 4 Mate-in-N tasks and 3 survival tasks. The Mate-in-N tasks involved a diverse set of concepts, with some game situations unbalanced in favor of the opponent, forcing conservative players to focus on defensive moves. The 3 survival tasks were all hopeless positions, where experts would generally prefer to resign. On completion of each task, subjects were asked to explain their understanding of the board situation, and the reason for their moves. We specifically asked them to identify opportunities, threats and possible moves that were considered, including those not taken.

Although we have only recently begun analysis of this data, some interesting phenomena are evident. The following are examples from two expert players who provided particularly clear explanations.



a) Valence b) Arousal



c) Pupil Diameter d) Emotion States

Figure 6: Subject Q6 (expert ELO 1950+) attempting to resolve a Task 8 (Very difficult). The spike in arousal, valence, pupil diameter and emotion states of fear and disgust correspond to a self-reported recognition that the situation was hopeless.

Figure 5 on page 9 shows an expert (subject Q6, ELO 1950+) resolving task 4 (moderately difficult mate-in-N) The subject rapidly recognized and confirmed the solution as is evident in a steady decrease in valence, arousal and contempt. A temporary rise in pupil size is evident during the final, confirmation phase.

Figure 6 (page 10) shows the same expert (Q6, ELO 1950+) addressing the extremely difficult task 8. The subject displays a sustained period of moderate valence and low arousal and decreasing contempt, followed by a steep drop in valence, a rapid spike in arousal and pupil size, and a sudden peak in disgust and fear as the subject recognizes that there is no good solution to the problem.

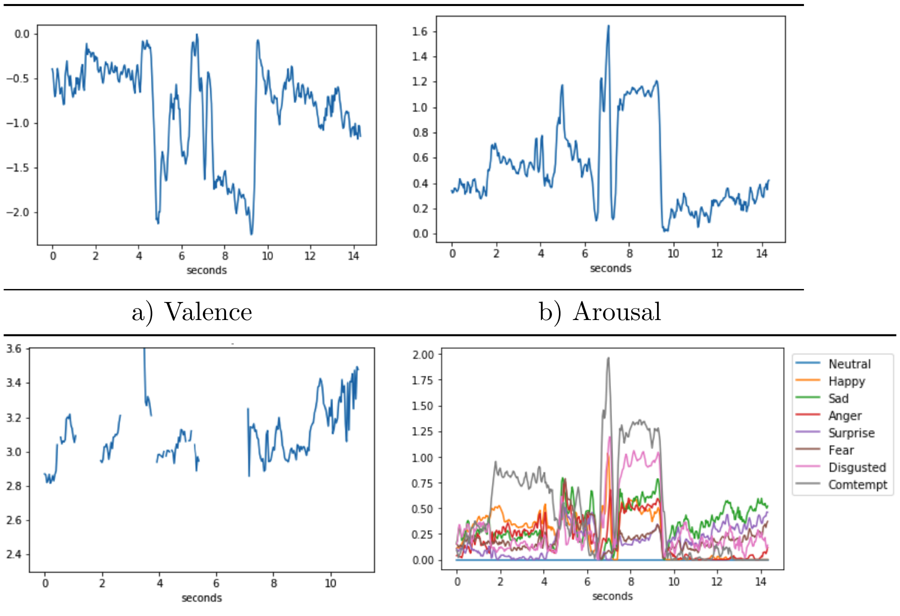
Figure 7 (page 11) shows a different expert (Q12, ELO 2000+) solving the moderately challenging Task 4. The moment where the subject recognizes the solution coincides with a strong correlation in valence, arousal, and contempt as well as a self-report of the solution. This is followed by a second, less intense period of increasing valence, arousal and contempt as the subject confirms the solution.

Figure 8 (page 11) shows subject Q12 (Elo 2000+) confronted with the hopeless situation of Task 8. The subject is visibly unhappy (strong negative valence), very excited (strong arousal), and disgusted until recognizing that the situation is hopeless after around 20 seconds. The rise in valence and drop in arousal can be interpreted as satisfaction as having successfully understood the game situation.

6 Conclusions

Results from our initial experiment with recording eye-gaze and emotion of chess experts showed an unexpected rapid variation of emotional state as experts solved challenging problems. In this paper we have proposed a model that explains this phenomena as an involuntary display of emotions associated with recognition of situations. Our model suggests that an association of emotions with recognized situations guides experts in their selection of partial game configurations for use in exploring the game tree. However, this is very much a work in progress, based on only limited data.

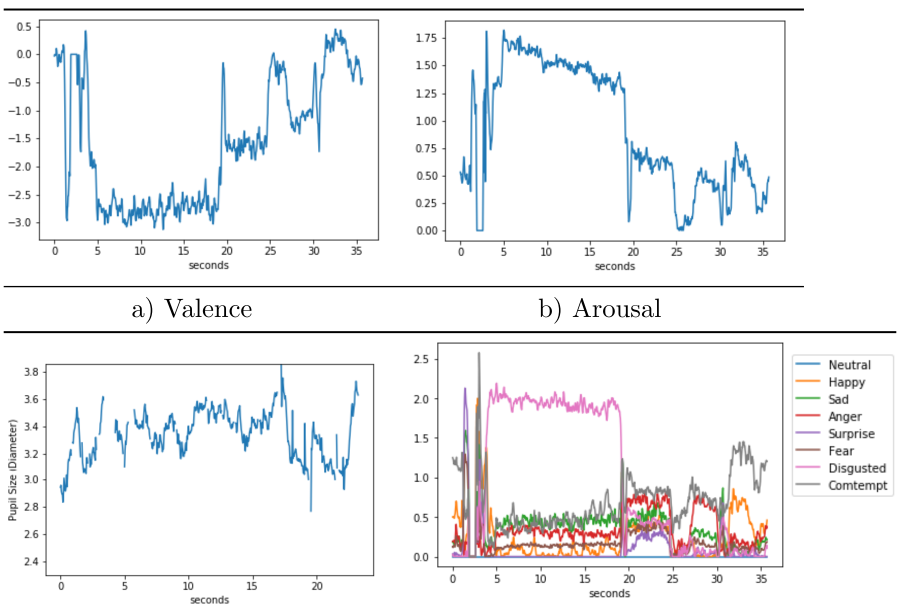
We have presented initial results from a follow-on experiment designed to explore the fidelity of our model, and to search for evidence of the role of emotion in solving challenging problems. Initial results from this second experiment appear to confirm our model. Further analysis and additional experiments are needed to more confidently model the role of emotions in reasoning.



a) Valence b) Arousal

c) Pupil Diameter d) Emotion States

Figure 7: Subject Q12 (expert ELO 2000) attempting to resolve Task 4. The moment where the subject discovers the solution is visible as a strong correlation in valence, arousal, and contempt as well as a self-report of the solution.



a) Valence b) Arousal

c) Pupil Diameter d) Emotion States

Figure 8: Expert Q12 (Elo 2000+) confronted with the hopeless situation of Task 8. The subject is visibly unhappy (strong negative valence), very excited (strong arousal), and disgusted until recognizing that the situation is hopeless after around 20 seconds.

ACKNOWLEDGMENT

This research has been be funded by the French ANR project CEEGE (ANR-15-CE23-0005), and was made possible by the use of equipment provided by ANR Equipment for Excellence Amiqual4Home (ANR-11-EQPX-0002). Access to the facility of the MSH-Alpes SCREEN platform for conducting the research is gratefully acknowledged. We are grateful to all of the volunteers who generously gave their time to participate in this study and to Lichess webmasters for their help and approval to use their platform for this scientific experience. We would like to thank Isabelle Billard, current chairman of the chess club of Grenoble "L'Échiquier Grenoblois" and all members who participated actively in our experiments. We also thank Professor Thomas Schack and Thomas Kchelmann of Univ. Bielefeld Dept of Neuro-Cognition, for valuable discussions and aid.

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